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An Optimized Graph-based Deep Learning Framework for Depression Detection Using EEG Signals

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Abstract: Depression is a serious psychiatric disorder that greatly impacts the quality of life and daily functioning of a person. Accurate diagnosis at the early stage is critical for success with intervention. Electroencephalography (EEG) offers a non-invasive technique to assess neurophysiological activity and is thus an important instrument for diagnosis of depression. Current EEG-based deep learning approaches are beset by high-dimensional data, poor feature selection, and poor classification performance owing to the nature of the EEG signal. To address these issues, we introduce EEGEffV2-SpikeNet, a new framework for depression detection that combines statistical feature extraction with deep feature extraction through a Graph Convolutional Network (GCN) approach. The proposed model incorporates a new fusion of statistical feature extraction and GCN-based deep feature learning for the extraction of both spatial and temporal EEG features. The extracted features are then optimized by the Modified Addax Optimization Algorithm (MAOA), a cutting-edge bio-inspired optimization algorithm that improves feature selection efficiency by discarding redundant information and enhancing classification accuracy. For depression classification, we utilize EfficientNetV2, Deep Belief Network (DBN), and Spiking Neural Network (SNN) to enhance feature representation and decision-making, leveraging the computational efficiency of EfficientNetV2 and the biologically plausible processing of SNN. Experimental results on two standard EEG datasets validate the better performance of the model, achieving 98.74% accuracy on Dataset 1 and 97.88% accuracy on Dataset 2, outperforming baseline models like DBN, EfficientNet, and SNN. The results prove the framework's promise as a dependable tool for objective and early depression diagnosis, with clinical application and mental health monitoring implications.

Index Terms: EEG, Depression Detection, Graph Convolutional Network, Modified Addax Optimization Algorithm, EfficientNetV2, Spiking Neural Network, Deep Learning.

1. Introduction

One of the most prevalent mental illnesses is depression, which is characterized by persistent sadness, low mood, and a loss of interest in activities. The increasing prevalence of mental illnesses, especially depressive disorder (DD) and generalized anxiety disorder (GAD), has drawn attention from a wide range of sectors. A significant and ongoing depressed mood is the primary characteristic of DD, and some patients engage in suicidal and self-harming behaviors [1]. Mental health challenges encompass mental disorders, psychosocial impairments, and other conditions associated with severe distress, functional impairment, or the risk of self-harm. Mental health issues are strongly associated with reduced levels of mental well-being [2,3]. Therefore, effective care and treatment for individuals suffering from mental health problems are essential. Individuals are more susceptible to depression when experiencing increased family and work-related stress. Cognitive difficulties and decreased concentration are prominent characteristics of this illness. The World Health Organization (WHO) estimates that 350 million people globally suffer from depression. Depression is projected to be among the leading causes of disability globally by 2030 [4,5].

Depression is divided into three severity categories: mild, moderate, and severe. Clinical signs of mild depression include sadness, anhedonia, fatigue, and difficulty concentrating, although these symptoms do not substantially disrupt the person's day-to-day activities. Moderate depression is associated with more severe symptoms, such as profound sadness, feelings of helplessness, low self-esteem, sleep disturbances, and changes in appetite [6]. Severe depression is characterized by suicidal ideation, severe sleep and eating disturbances, hopelessness, and significant impairment in daily functioning. Depression persistently affects mental, physical, and emotional health. Depression is commonly characterized by melancholy, decreased energy or pleasure, changes in eating or sleeping patterns, difficulty concentrating, feelings of insignificance or remorse, and thoughts of self-harm or self-destruction [7,8]. The use of automated objective evaluation techniques to improve mental health diagnosis and detection has recently been extensively researched. Effective treatment of depression depends on early detection and diagnosis [9].

The cost-effectiveness, high temporal resolution, non-invasiveness, and utility of EEG technology have made it a powerful tool for studying neurological disorders. To distinguish between individuals with depression and healthy controls, numerous studies have used a variety of feature selection and classification strategies based on EEG data. EEG's great temporal resolution and ease of acquisition have made it a popular physiological technique for emotion identification tasks. EEG signals are collected by placing electrodes on the scalp to record the electrical activity of the underlying brain tissue [10,11]. Since emotional processing is closely linked to brain activity recorded by EEG, analyzing these signals is significant for emotion recognition research. EEG properties have been shown to be useful for analyzing brain activity in a variety of mental illnesses. Because the EEG records the electrical impulses produced by brain neurons, it is a useful tool for examining brain activity and identifying anomalies linked to depression [12,13]. Resting-state EEG, a neuroimaging method noted for its excellent temporal resolution, shows potential for predicting treatment response in depressive disorders. High temporal resolution, cost effectiveness, and non-invasiveness are its advantages. However, the great dimensionality and complexity of these signals make it difficult for ML/DL models to directly analyze them. Several feature extraction and reduction strategies have been used by the researchers to analyze EEG signals [14,15].

In recent years, some studies have successfully employed machine learning (ML), particularly deep learning (DL) based methods, for the identification of depression. Rapid advancements in artificial intelligence, particularly deep learning models, have demonstrated tremendous potential for the early identification of depression. Depression is often indicated by a patient's language use, vocal intonation, facial emotions, and other behavioral clues [16]. EEG's limited spatial resolution and noise sensitivity have historically prevented it from being fully utilized, despite its great temporal resolution. However, new developments in computational methods, including low-resolution electromagnetic tomography (LORETA), have enabled better spatial resolution by estimating the position of sources of brain activity [17,18]. Training Spiking CNNs is challenging, which is one of their drawbacks. Spiking networks on neuromorphic hardware show this behavior. These networks are typically trained as regular (non-spiking) CNNs and then converted to spiking networks to circumvent the difficulties associated with direct training [19,20].

The following are the major contributions of this work:

- We develop a robust preprocessing pipeline, including notch filtering, Wavelet Packet Transform (WPT), and Canonical Correlation Analysis (CCA), to clean EEG signals and remove artifacts.
- We introduce a Graph Convolutional Network (GCN) to model brain connectivity and a Modified Addax Optimization Algorithm (MAOA) for feature selection, enhancing classification accuracy by reducing redundancy.
- We propose EEGEffV2-SpikeNet, a novel hybrid deep learning framework combining EfficientNetV2, DBN and Spiking Neural Networks (SNNs) to improve EEG-based depression detection through efficient spatial-temporal feature learning.

The remainder of this paper is organized as follows: Section 2 reviews related works. Section 3 describes the proposed methodology. Section 4 presents the experimental results. Section 5 concludes the paper.

2. Related Works

Alenizi et al. (2024) [21] presented a new model that integrates a dictionary learning method with NeuCube architecture to analyze the contributions of various brain areas to depression. To detect patterns associated with depression, NeuCube simulates neural events across multiple brain areas and integrates dictionary learning with the resultant spike train outputs. This hybrid strategy maintains excellent separation power for the diagnosis of depression while allowing a high level of interpretability regarding the contributions of biology and connection. Liu et al. (2025) [22] proposed the Domain Adversarial Learning Framework for Major Depressive Disorder Diagnosis (MDD-DAL), which utilizes a spatial-temporal transformer architecture to extract significant brain spatial-temporal features from EEG signals, thereby overcoming the limitations of CNNs and RNNs. In addition, the model's generalizability to variations in EEG data of other subjects is enhanced through domain adversarial learning methods. An MDD diagnosis dataset was employed to validate the model, which demonstrated superior classification performance.

Chung et al. (2024) [23] introduced a new multi-level ensemble learning method that combines multiple EEG bands for depression and mental state assessment. Eight sub-bands were initially derived from the EEG signals, and each band was processed using a Deep Neural Network (DNN) incorporating Long Short-Term Memory (LSTM) units. A two-stage ensemble learning technique based on Multiple Linear Regression (MLR) is then used to assess mental state or the severity of depression after combining multi-band EEG frequency models. To validate the efficacy of the suggested method with diverse evaluation criteria, the authors performed a large number of experiments. Gan et al. (2025) [24] developed TSF-MDD, a novel deep learning method that integrates frequency-, spatial-, and temporal-domain data. To obtain a four-dimensional temporal-spatial-frequency representation of EEG signals, TSF-MDD initially applied a data reconstruction strategy. A 3D-CNN and CapsNet-based model subsequently process the data, facilitating thorough feature extraction from many domains. Lastly, in order to avoid data leaking when training and testing, a subject-independent data partitioning strategy was employed.

Chen et al. (2024) [25] proposed a technique called the Dual Attention Mechanism Graph CNN (DAMGCN). To extract representative spatial information, the authors used a GCN to model the brain network as a graph. Additionally, the self-attention mechanism of the Transformer model was utilized to assign higher weights to significant brain regions and frequency bands. The attention mechanism visualization makes the weight allocation that DAMGCN learned very evident. Li et al. (2024) [26] aimed to enhance diagnostic processes and facilitate early patient identification by proposing a lightweight detection technique for multiple mental diseases using limited data sources. To create the entropy-based matrix, the suggested method first uses Electroencephalography (EEG) data as sources, then uses Discrete Wavelet Decomposition (DWT) to learn brain rhythms and extract their approximate, fuzzy, permutation, and sample entropy.

Abidi et al. (2024) [27] proposed a new automatic deep learning method using EEG data for depression diagnosis. Three sets of features were extracted from the original EEG signals after collecting necessary samples from publicly accessible databases. In this process, spectrogram images were generated, spectral features were extracted, optimal weights were combined, and a 3D-CNN was used for deep features while a 1D-CNN was used for 1D features. The Chaotic Owl Invasive Weed Search Optimization (COIWSO) algorithm was developed to select the best features. The Self-Attention-based Gated Densenet (SA-GDensenet) is then used to analyze the fused features in order to detect depression. The same COIWSO helps to optimize the parameters within the detection network.

Liu et al. (2024) [28] introduced a new approach for depression diagnosis based on electrode spatial topology and time-frequency complexity. First, the temporal features and time-frequency complexity of the EEG signal were obtained to construct node features for a GCN. Lastly, channel correlation is used to calculate the brain adjacency matrix. GCN was trained and tested with graph node features and a brain network adjacency matrix based on channel correlation to arrive at the final depression classification. Shen et al. (2024) [29] developed a brain-inspired hemisphere asymmetry network (HEMAsNet) for depression identification from EEG signals. For extracting temporal features from the two hemispheres of the brain, HEMAsNet used LSTM blocks with multi-scale CNN blocks. Furthermore, the model introduced a new "Callosum-like" block, motivated by the corpus callosum's important role in facilitating inter-hemispheric information transfer. This block can enhance the precision of depression recognition by making the exchange of information between the hemispheres more accurate.

Xing et al. (2024) [30] introduced EMO-GCN, an adaptive multigraph neural network-based multimodal depression detection technique. The potential correlations among modalities are disclosed by representing data from various modalities in a graph-based manner and then extracting features from them. Graph convolutional layers and graph pooling layers are regarded as a fundamental unit. Three-way stacking of the units enables us to develop multi-GCN, the core element of EMO-GCN. With this configuration, the model can identify sorrow with high accuracy and investigate possible relationships between audio and EEG data by combining important components from several modalities using an attention mechanism. Penava and Buettner (2024) [31] used a 1D CNN and deep learning to create a model capable of recognizing moderate depression in resting-state EEG data. In this study, a novel method was demonstrated for using resting-state EEG data to detect mild depression early using DL. Through SIEPTNet, a novel 1D CNN architecture was showcased that saves resources while producing encouraging results with a balanced accuracy of nearly 70%.

Bhanja et al. (2024) [32] presented a novel CNN with Bat Optimization (CN-BO) structure to determine the human brain's stress level. In addition, various processing methods are integrated into this study to distinguish the stress state. In the classification layer, the bat optimization algorithm was applied to improve the precision of stress level classification. Finally, the created CN-BO approach uses the normal dataset to classify the patient's stress rate. As a result, the MATLAB platform is used to implement the suggested model. Ying et al. (2024) [33] created a lightweight attention mechanism that uses fewer model parameters and requires less computing power by modifying the conventional multi-head self-attention mechanism. A DL model called the Functional Connectivity Attention Network (FCAN) is also built employing this lightweight attention approach. FCAN uses the coherence matrix of EEG data to effectively identify depression. The two main parts of FCAN are the feature integration module, which combines extracted features, and the spatial attention module, which extracts deep spatial properties from EEG data.

De et al. (2024) [34] proposed a new linear GCN-transformer-based method that uses EEG signal time-frequency analysis to classify MDD. For MDD diagnosis, the resulting 2D representation is input into a specially designed Linear GCN after the spectro-temporal information from the EEG is exploited using the Stockwell transform (S-transform). To enhance learning and manage unbalanced input, the Weighted Focal Binary Hinge Loss function was employed, which is accurately made for tailored Linear GCN. A new Transformer model is then created in order to further refine the MDD classification. SLiTRANet, the suggested methodology, combines the S-transform for spectral analysis, the Transformer's sequence modeling capabilities, and Linear Graph Convolution Network for graph-based learning.

Conventional machine learning and deep learning approaches fail with these challenges, which usually lead to weak feature selection, redundancy, and poor classification performance. Recent breakthroughs in graph-based deep learning, optimization techniques, and hybrid models have potential to overcome these shortfalls, but there are still gaps to reach robust, interpretable, and computationally effective solutions. The review of the literature underscores the necessity for a holistic framework encompassing enhanced preprocessing methods, best feature selection, and ensemble DL models in order to improve the accuracy, efficiency, and generalizability of EEG-based depression diagnosis systems.

2.1. Problem Statement & Motivation

Despite the major progress in the use of EEG in the detection of depressions, existing methods still experience serious limitations. The main research problem this work aims to resolve is inefficient extraction and selection of meaningful spatial-temporal features from an EEG signal. This typically results in redundant feature representation, inefficient accuracy of the classification process, and high computations. Traditional machine learning algorithms are heavily dependent on manually designed features, which cannot model the intricate non-Euclidean connectivity patterns in the brain, while many deep learning algorithms tend to be prone to overfitting, lack interpretability, and generalize poorly across the subjects owing to inappropriate feature optimization. Moreover, it has been noticed that the majority of existing depression recognition systems based on EEG signals have been dealing independently with spatial, temporal, and frequency-related information, without making use of any existing functional brain connections. Though some emerging graph models as well as spiking neural network models have appeared quite promising, they have often been quite complex from a computational point of view. Based on the above challenges, this research proposes to design an efficient, connectivity-considered, and optimized hybrid deep learning model, which is capable of simulating EEG spatiotemporal features, reducing irrelevant features through intelligent optimization, and improving classification stability.

2.2. Research Gaps

Despite the fact that newer studies have shown the efficiency of using machine-learning models and deep learning models based on EEG for the detection of depression, it has been found that a critical analysis of the existing models has a number of unresolved limitations. Current models mostly concentrate only on a single domain of feature extraction. Almost all previous studies tend to enhance the accuracy of detection either through hand-crafted feature extraction or through modular deep learning approaches like convolutional networks, recurrent networks, or attention networks. Though these methods prove to be quite fruitful, they still remain localized and neglect the diverse dependencies among the EEG features present in the spatial, temporal, and frequency domains. Moreover, existing approaches tend to utilize fixed representations or connectivity patterns, which are insufficient in capturing the dynamic and nonstationary nature underlying the EEG signal.

Techniques involving graph networks as well as hybrid deep networks have emerged in handling the spatial aspect; however, they tend to make use of predefined or correlation-derived adjacency matrices. Furthermore, the techniques used in feature selection and optimization are often utilized in a separate preprocessing process rather than being combined in a way with deep feature learning, leading to redundant features. Another related limitation can be observed with an increase in model complexity. Several high-performing methods have achieved better accuracy while increasing their training cost, large number of parameters, and high inference latency, hence limiting their applicability in real-time or resource-constrained environments. Contrary to the above challenges, the proposed approach is intended to tackle the above research gaps by incorporating an efficient framework that combines learning of adaptable features, optimization-driven refinement of features, and efficient classification. By modeling spatial and temporal EEG patterns, as well as optimizing redundant features, the proposed approach is expected to improve the accuracy of detection while remaining computationally efficient.

3. Proposed Methodology

The proposed method of depression detection based on EEG signals starts with preprocessing, in which raw EEG signals are filtered through a notch filter to eradicate power line noise, separated into sub-bands through Wavelet Packet Transform (WPT), and then cleaned again using Canonical Correlation Analysis (CCA) to remove artifacts, leading to clean, artifact-free data. The pre-processed signals are then made ready for feature extraction, wherein statistical features (e.g., mean, variance, PSD) and deep learning-based features are extracted through a Graph Convolutional Network (GCN) to identify spatial-temporal patterns in brain connectivity. The extracted features are then optimized by the Modified Addax Optimization Algorithm (MAOA) to remove redundancy and enhance classification accuracy. The chosen features are then input into the EEGEffV2-SpikeNet model, that utilizes EfficientNetV2, DBN for effective feature extraction and Spiking Neural Networks (SNNs) for temporal pattern recognition, resulting in a probability distribution output through a softmax layer to classify EEG signals as depressed or non-depressed. This holistic approach provides accurate and efficient depression detection using EEG data. Fig 1 demonstrates the block diagram of the proposed methodology for depression detection, outlining the workflow from preprocessing to classification.

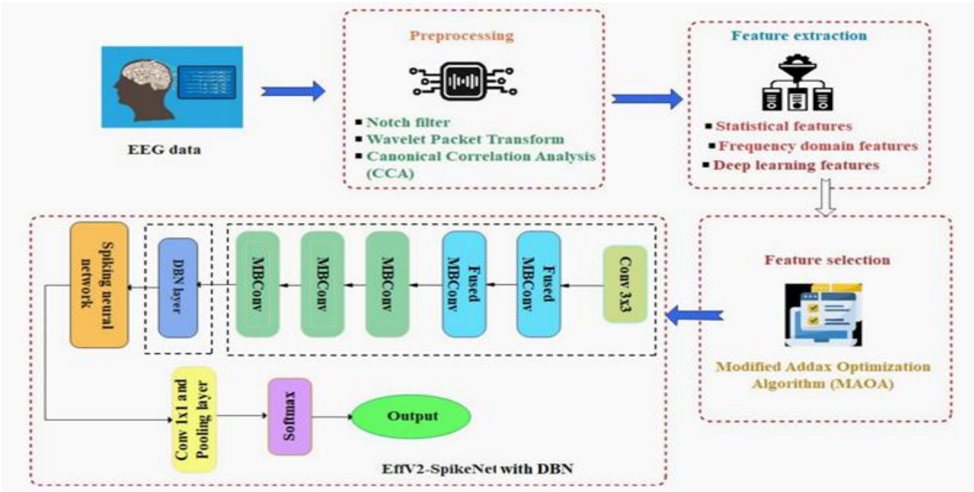

Fig.1. Block diagram of the proposed EEGEffV2-spikenet framework for depression detection

Initially, raw EEG signals will be collected using multi-channel EEG datasets. The signals will then go through some preprocessing techniques, which include utilization of notch filtering as a method to reduce power-line interference, Wavelet Packet Transform as a mean to segment the signals into appropriate sub-bands, and Canonical Correlation Analysis to reduce artifacts like eye blinking and muscular artifacts. After that, cleaned EEG signals are used for informative feature extraction, including statistical time- and frequency-domain features that can capture the distribution and spectral characteristics of the signal. Deep features were learned by a Graph Convolutional Network (GCN), modeling the brain as a graph for effective learning of the spatial and functional connectivity patterns between the EEG channels. Third, the derived features will be further optimized using MAOA, which selects only those relevant features that do not lead to redundancy, reducing computational complexity, hence enhancing classification performance. Finally, the optimized features are passed on to the EEGEffV2-SpikeNet classifier, which combines EfficientNetV2 for efficient learning of spatial features, Deep Belief Network (DBN) for learning high-level features, and Spiking Neural Network (SNN) for learning temporal information. The model produces a binary output representing depressed or non-depressed classes.

3.1. Preprocessing

The initial stage of the methodology is preprocessing, which is needed to pre-prepare the raw EEG signals for analysis. EEG signals tend to be noisy and have artifacts that can cause problems in proper analysis. The choice of preprocessing methods in this work is driven by the nature of the EEG data and the electroencephalographic markers of the depressed state. The nature of EEG data is prone to power-line artifacts, nonstationary, and other biological phenomena such as eye and muscle activities. The notch filter is hence utilized as a first step in effectively removing narrowband power-line noise (50/60 Hz) without affecting the useful EEG frequencies. Subsequently, the Wavelet Packet Transform (WPT) is utilized for its better capacity in dealing with the non-stationarity of the EEG signal and offering finer resolution in the time-frequency domain. This is even more relevant in the context of depression, wherein delta, theta, alpha, and beta abnormalities have all been observed together in depressive disorders. Finally, Canonical Correlation Analysis (CCA) is employed for removing artifacts owing to its data-driven nature and its capability to identify and remove noise without using reference channels. In contrast to the traditional filtering approach, the notch filtering, WPT, and CCA joint approach makes it possible to suppress noise comprehensively, remove the crucial frequency parts, and improve the signal-to-noise ratio. The optimized processing flow helps to ensure that the deep learning approach and feature extraction are conducted from high-quality EEG maps, which is conducive to the improvement in the classification accuracy achieved in the proposed approach.

A. Notch Filter

A notch filter is applied at 50 Hz or 60 Hz, depending on the area where the data was taken, to remove power-line noise. A notch filter is a form of band-stop filter that eliminates an extremely narrow frequency band while all other frequencies are left unaltered. Although band-pass filters are set up to allow an interval of frequencies to be transmitted, notch filters have the opposite effect: they will cancel out a single frequency that is well defined. The notch filter equation is given by Eqn (1):

$$H(f) = \frac{s^2+\omega^2}{s^2+\frac{\omega s}{Q}+\omega^2} \tag{1}$$

The notch frequency (50 or 60 Hz) is represented by ω. The quality factor that regulates the notch's bandwidth is called Q. The quality of the data for feature extraction is improved by using a notch filter, which guarantees that power-line noise is successfully eliminated without causing distortion to the EEG signals

B. WPT

Once power line noise is removed, the EEG signals are decomposed into sub-bands via the Wavelet Packet Transform (WPT). WPT is a wavelet transform (WT) extension that may be applied to multi-resolution analysis to get insight into EEG signals. Delta (0.5–4 Hz), alpha (8–12 Hz), gamma (>30 Hz), theta (4–8 Hz) and beta (12–30 Hz) signals are the most common types found in EEG recordings. WPT typically decomposes EEG signals to distinguish between different EEG rhythms. Given that the frequency of the final decomposition level is about 4 Hz, the formula $f_s/2^{l+1} \leq 4$ must be satisfied assuming that the wavelet packet analysis layer level is l and the EEG sampling rate is f_s. The mother function used in this study to break down and rebuild each channel of the EEG data was the Symlet wavelet of order 5 (Sym5), with l being chosen as the smallest value that met the previous requirement. Through the decomposition of the signals into these sub-bands, the model can concentrate on the most informative frequency components for detecting depression.

C. CCA

The last preprocessing step is the use of Canonical Correlation Analysis (CCA) to eliminate artifacts like eye blinks, muscle activity, and other non-brain-related signals. CCA is commonly employed to examine the relationship among two sets of multivariate random variables. It is a variant of the correlation between two random variables under two sets of random variables. The correlation coefficients for two random variables, x and y, are defined as follows:

$$\rho = \frac{Cov(x,y)}{\sqrt{D(x)D(y)}} \tag{2}$$

where the variance of x, y is denoted by $\sqrt{D(x)D(y)}$ and the covariance by $Cov(x,y)$. CCA addresses the relationship between two random variable sets, X and Y, by determining a specific linear combination of the two sets, respectively. Equations (3) demonstrate:

$$x' = a^T X \qquad y' = b^T Y \tag{3}$$

where the linear combination of X and Y is represented by x' and y'. To maximize the correlation coefficient between x' and y', CCA seeks to determine the values of a and b.

$$\underset{a,b}{argmax\rho} = \underset{a,b}{argmax} \frac{Cov(a^T X, b^T Y)}{\sqrt{D(a^T X) D(b^T Y)}} \tag{4}$$

Equation (4) can be changed into Equation (5) since X and Y are preprocessed multi-dimensional variables with a variance of 1 and a mean of 0.

$$\underset{a,b}{argmax} \frac{a^T Cov(X,Y) b}{\sqrt{a^T D(X) a}\sqrt{b^T D(Y) b}} \tag{5}$$

This preprocessing step is essential for guaranteeing that the analysis to follow is based on clean and relevant EEG data. After the EEG signals are preprocessed, the subsequent step is data preparation. During this step, the preprocessed EEG data is ready for feature extraction. This step formats the EEG signals for subsequent feature extraction and classification.

3.2. Feature Extraction

The feature extraction process is one of the most important components of the methodology. In this stage, meaningful features are extracted from the EEG signals that can be utilized to differentiate between depressed and non-depressed subjects. The feature extraction process is divided into two categories: statistical feature extraction and deep learning-based feature extraction. Several features of brain activity are extracted from EEG signals to determine patterns and characteristics necessary for further analysis. This process employs multiple methods to derive meaningful information from raw EEG data.

A. Time-domain Features

Statistical properties such as mean, skewness, variance, and kurtosis are calculated in time-domain analysis. Mean describes the central tendency of the EEG signal while variance measures the spread or dispersion of the signal. These statistical parameters reveal information on the central tendency, variability and asymmetry of EEG signals as well as offer a glimpse into the underlying neural dynamics and their time-varying behavior.
Mean (μ): The mean value of the EEG signal is calculated using the following formula:

$$\mu = \frac{1}{N}\sum Y_i \tag{6}$$

where N signifies the total number of samples in the signal and Y_i is the ith sample.

Variance ($\boldsymbol{\sigma^2}$): Variance is the measure of the spread or dispersion of the EEG signal and is calculated as follows:

$$\sigma^2 = \frac{1}{N}\sum(Y_{i-}\mu)^2 \tag{7}$$

where N is the sample count, Y_i is the i-th sample, and μ is the signal's mean.

Skewness: Skewness is a degree of the asymmetry of the distribution of the EEG signal and is calculated by the following formula:

$$Skewness = \frac{\frac{1}{N}\sum(Y_{i-}\mu)^3}{\sigma^3} \tag{8}$$

where N is the sample count, Y_i is the i-th sample, μ is the mean, and σ^3 is the standard deviation's cube.

Kurtosis: Kurtosis is the degree of the peak or flatness of the EEG signal distribution and is calculated as:

$$Kurtosis = \frac{\frac{1}{N}\sum(Y_{i-}\mu)^4}{\sigma^4} \tag{9}$$

where the sample count is denoted by, and stands for sample numberNY_i i, μ denotes the mean, and σ^4 denotes the standard deviation's fourth power.

B. Frequency Domain Features

Frequency domain features, such as Power Spectral Density (PSD) and spectral entropy, investigate the frequency component distribution in EEG signals. These parameters are computed from the frequency content of the signals. PSD offers details on how power is distributed across various frequency ranges, and spectral entropy estimates the complexity and randomness of the frequency content of the signal. PSD reveals dominant frequencies and their magnitudes.

Power Spectral Density (PSD):

The PSD of the EEG signal illustrates how the power is spread over different frequency bands. The signal's Fourier transform is used to calculate the PSD, whose formula is as follows:

$$PSD = |FFT(Y(f)|^2 \tag{10}$$

where $|FFT(Y(f)|^2$ denotes the magnitude squared of the Fourier coefficients and $(Y(f)$ is the EEG signal's Fourier transform.

C. GCN for Deep Learned Features

In addition to statistical characteristics, deep learning-based features are extracted using a Graph Convolutional Network (GCN). GCN plays an essential role in extracting the spatial-temporal patterns in EEG signals. Compared to traditional CNNs that process data in grid-like form, GCNs process data in a graph-structured format and are thus suitable for representing the functional connectivity of the brain. The GCN extracts spatial-temporal patterns from EEG signals by modeling the brain as a graph, where every node is a brain region and the edges are the connectivity between brain regions. Graph Convolutional Networks (GCNs) are utilized within this work to effectively capture the naturally available spatial relations between the EEG electrodes. Conventional grid-based deep learning architectures are not able to effectively represent the functional EEG electrode relations. EEG signals are recorded using electrodes positioned irregularly on the scalp. The relationships between EEG electrodes reflect brain connectivity. To model this structure effectively, the EEG system is modeled as a graph, whose nodes are the locations or points of an EEG electrode (or area of the brain), and whose edges model relationships such as correlation or coherence between the electrodes. In contrast to conventional CNNs, designed under a grid-like assumption for a regular spatial architecture, GCNs directly handle graph-structured data and update node feature representations by aggregating information from neighboring nodes. In terms of EEG analysis, it helps in understanding the influence of activity in a node on activity in other nodes with similar functional and anatomical properties. Each layer of the GCN updates the representations of nodes by integrating local features of EEG signals with information propagated from connected electrodes, learning spatial dependency patterns related to depression.

A GCN is a multilayer neural network that processes directly on a graph and outputs node embedding vectors based on neighbor attributes. Take a graph $G = (V, E)$, where V is the edge set of the graph and E is its node set. Suppose that $Y \in \mathcal{R}^{m \times n}$ is a matrix that contains all the nodes and their features, and the dimension of the feature vectors is m. The GCN layer can be described as

$$L^{(j+1)} = \rho\left(\tilde{A}L^{(j)}W_j\right) \tag{11}$$

$\rho(\cdot) D_{ii} = \sum_j A_{ij}\, \tilde{A} = D^{-1/2}AD^{-1/2} W L^{(0)} = Xj = 0$ where is an activation function, is a degree matrix, is the normalized symmetric adjacency matrix, and is a weight matrix. in the event that (the input layer). The GCN generates node embedding vectors from the attributes of the neighboring nodes, which allows it to learn fine-grained patterns in the EEG data that could not be identified using statistical features. Furthermore, the GCN's ability to deal with non-Euclidean data makes it particularly efficient in the context of EEG analysis, in which electrode positions form an irregular graph. Collectively, these features provide a more discriminative, richer representation of EEG signals, thereby enhancing the model's performance in depression detection. By integrating GCN-extracted features with time and frequency-domain features, the model gains comprehensive information regarding localized and global brain activities. The integration of these approaches makes the model more effective in detecting subtle depression-related patterns such as altered connectivity or abnormal neural oscillations, leading to improved classification accuracy and resilience. The proposed framework combines GCN-based features with conventional time- and frequency-domain EEG features, thus capturing both the localized signal characteristics and global brain connectivity patterns. This combination clearly improved interpretability and classification performance, hence making GCNs particularly suitable for EEG-based depression detection.

3.3. Modified Addax Optimization Algorithm for Feature Selection

Once the features are acquired, the next step is feature selection. Here, the features extracted are streamlined to eliminate irrelevant or redundant features, which will make the model more accurate and efficient. The feature selection mechanism is implemented through the Modified Addax Optimization Algorithm (MAOA), which is a bio-inspired optimization. The MAOA is designed for maximizing the feature selection effectiveness through iteratively updating the list of features. MAOA is selected over traditional metaheuristic methods such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) due to its balanced exploration-exploitation trade-off, less dependency on the method parameters, and more convergence towards the global optimum. EEG-based depression classification requires the extraction of a massive number of diverse feature vectors, and the presence of redundant and correlated features can significantly increase noise in the model and deteriorate classification performance. GA may face the challenge of premature convergence and high computational costs because of the process of crossover and mutation. Moreover, the convergence of PSO to local optima is highly dependent on the choice of the velocity factor when the number of features increases. In contrast, MAOA utilizes biologically inspired foraging and weighted Lévy flight-based digging mechanisms that allow efficient global exploration in early iterations and refined local exploitation at later stages. This adaptive search behavior is particularly suitable for feature selection problems in which optimal subsets are sparse and nonlinearly distributed. Moreover, MAOA has fewer control parameters than GA and PSO, which reduces the tuning complexity and enhances stability across data sets.

The proposed Addax Optimization Algorithm (AOA) [35] is a population-based metaheuristic algorithm where the population consists of addaxes. AOA is excellent at using its members' search ability to deliver efficient solutions to optimization difficulties through an iterative method. Each addax represents a candidate solution by assigning values to the design variables within the search space. Thus, each addax's position in the search space represents a potential solution to the problem. Each addax's location, which is regarded as a potential solution, can be expressed as a vector whose length is equal to the number of choice variables. Furthermore, Eq. (12) allows for the formal modeling of the AOA population as a matrix, which includes addaxes and the vectors that correspond to them. According to Eq. (13), the addaxes' initial positions in the problem-solving space are chosen at random.

$$A = \begin{bmatrix} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_N \end{bmatrix}_{N\times m} = \begin{bmatrix} a_{1,1} & \cdots & a_{1,d} & \cdots & a_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ a_{i,1} & \cdots & a_{i,d} & \cdots & a_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ a_{N,1} & \cdots & a_{N,d} & \cdots & a_{N,m} \end{bmatrix}_{N\times m} \tag{12}$$

$$a_{i,d} = lb_d + r.(ub_d - lb_d) \tag{13}$$

A indicates the population matrix of AOA, A_i refers to the ith addax (candidate solution), and $a_{i,d}$ represents its dth dimension in the search area (decision variable). r is an arbitrary number within the interval [0,1], while symbolizes the number of addaxes in the population$N$, m is the count of decision variables, lb_d and ub_d stand for the lower and upper bounds of the dth decision variable, correspondingly. It is possible to evaluate the corresponding objective function for each addax since each addax's position acts as a potential solution. According to Eq. (14), the values assessed for the objective function form a vector.

$$Fit = \begin{bmatrix} Fit_1 \\ \vdots \\ Fit_i \\ \vdots \\ Fit_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} Fit(FS_1) \\ \vdots \\ Fit(FS_i) \\ \vdots \\ Fit(FS_N) \end{bmatrix}_{N\times 1} \tag{14}$$

Fit signifies the vector of assessed objective functions, where Fit_i indicates the assessment of the objective function based on the ith addax.

The AOA is inspired by the addax's ability to track rainfall and locate foraging sites with abundant vegetation. This animal is also highly skilled in digging to make appropriate depressions for resting and coping with sandstorms. The design of AOA was mostly inspired by these ingenious addax behaviors. In each iteration, the position of each addax is updated through two phases: (i) exploration, simulating the foraging behavior, and (ii) exploitation, simulating the digging behavior.

Phase 1: Foraging process

During the initial stage of AOA, the population members' positions in the problem-solving domain are modified by mathematically modeling the changes in the addaxes' locations during foraging. Addaxes inhabit arid regions and primarily feed on grasses, shrub leaves, legumes, and herbs. Their capacity to monitor rainfall and identify regions with a profusion of flora enables them to forage skillfully. Addaxes look for food sources independently and thoroughly even when they are a part of a herd. The placements of population members within the problem-solving area significantly alter as a result of AOA's modeling of the significant shifts in addaxes' positions during foraging. According to Eq. (15), each addax in the AOA design takes into account the locations of other addaxes with higher objective function values as appropriate foraging regions.

$$CL_i = \{A_k : Fit_k < Fit_i \ and \ k \neq i\} \tag{15}$$

where i=1,2,…,N and k∈{1,2,…,N}. The set of possible locations with suitable vegetation for the ith addax's foraging is represented by CLi. Ak signifies the population member with a better objective function value compared to the ith addax, and $Fitk$ represents its objective function value. Every individual in the AOA population has a new location determined by Eq. (16), which models addax movement towards appropriate vegetation zones throughout the foraging phase. According to Eq. (17), the associated member's prior position is then superseded if the objective function value increases as a result of this new position.

$$a_{i,j}^{P1} = A_{i,j} + r_{i,j}.\left(SL_{i,j} - I_{i,j}.A_{i,j}\right) \tag{16}$$

$$A_i = \begin{cases} A_i^{P1}, & Fit_i^{P1} \leq Fit_i \\ A_i, & else \end{cases} \tag{17}$$

SL_i represents the chosen area for foraging by the ith addax. The newly calculated position for the ith addax, derived from the foraging phase of the proposed AOA, is implied by A_i^{P1}, where $a_{i,j}^{P1}$ denotes its jth dimension. $SL_{i,j}$ represents its jth dimension in that area. Additionally, $r_{i,j}$ symbolizes random numbers drawn from the interval [0, 1], and $I_{i,j}$ represents numbers that are chosen at random and have values of 1 or 2. Fit_i^{P1} relates to the objective function value for the ith addax in this stage

Phase 2: Weighted Lévy-based digging skill

Addaxes rest in the depressions they have made and begin digging in shaded areas during the day. Addaxes are additionally shielded from sandstorms by the digging process and the depressions. Slight positional adjustments are made by the addaxes during the digging process. The algorithm's exploitation potential for efficient local search management is increased when these little positional changes during digging are modeled, which results in matching small variations in the positions of AOA population members within the problem-solving area. Eq. (18) is used in the AOA design to calculate a new location for every member of the AOA population, taking into account the modeled changes in addax positions during digging. According to Eq. (19), the linked member's prior location is then replaced if the new position raises the objective function value.

$$a_{i,j}^{P2} = A_{i,j} + \left(1 - 2r_{i,j}\right).\frac{ub_j - lb_j}{t} \times RL \tag{18}$$

$$A_i = \begin{cases} A_i^{P2}, & Fit_i^{P2} \leq Fit_i \\ A_i, & else \end{cases} \tag{19}$$

Weighted Lévy flight, denoted as "RL," is used to improve the algorithm's optimization accuracy.

$$RL = 0.5 \times Levy(Dim) \tag{20}$$

The Lévy flight distribution function is represented by $.Levy(Dim)$ The following formula (21) is used to calculate it:

$$Levy(D) = s \times \frac{u \times \sigma}{|v|^{\frac{1}{\eta}}} \tag{21}$$

The fixed constants s and η in this case are 0.01 and 1.5, respectively. Two random numbers in the interval [0, 1] are u and v. Here is the formula for σ:

$$\sigma = \left[\frac{\Gamma(1+\eta) \times \sin\left(\frac{\pi\eta}{2}\right)}{\Gamma\left(\frac{(1+\eta)}{2}\right) \times \eta \times 2\left(\frac{\eta-1}{2}\right)}\right]^{\frac{1}{\eta}} \tag{22}$$

In this case, η is equal to 1.5 and Γ represents the gamma function. A_i^{P2} indicates the newly intended location for the ith addax, obtained from the digging stage of the suggested AOA, $a_{i,j}^{P2}$ symbolizes its jth dimension, Fit_i^{P2} relates to its objective function value, and represents the current iteration.t

The location of each addax within the problem solution space is modified in accordance with the foraging and digging stages to complete the first iteration of AOA. After that, the algorithm advances to the subsequent iteration with the changed goal function values and addax placements, using Eqs. (4) to (8) for additional improvements until the last iteration. Every iteration saves and updates the best solution found thus far. The ideal solution found during the algorithm's rounds is the final AOA solution for the specified problem.

3.4. EEGEffV2-SpikeNet for Classification

The last stage of the approach is classification, where the selected features are passed to the EEGEffV2-SpikeNet model for the detection of depression. EEGEffV2-SpikeNet is a deep neural architecture that integrates the strengths of EfficientNetV2 and Spiking Neural Networks (SNNs). It serves as a state-of-the-art framework for depression recognition from EEG signals. It inherits the strengths of EfficientNetV2 and SNNs for effective processing and classification of high-dimensional EEG data. Fig. 2 illustrates the detailed architecture of the EEGEffV2-SpikeNet model.

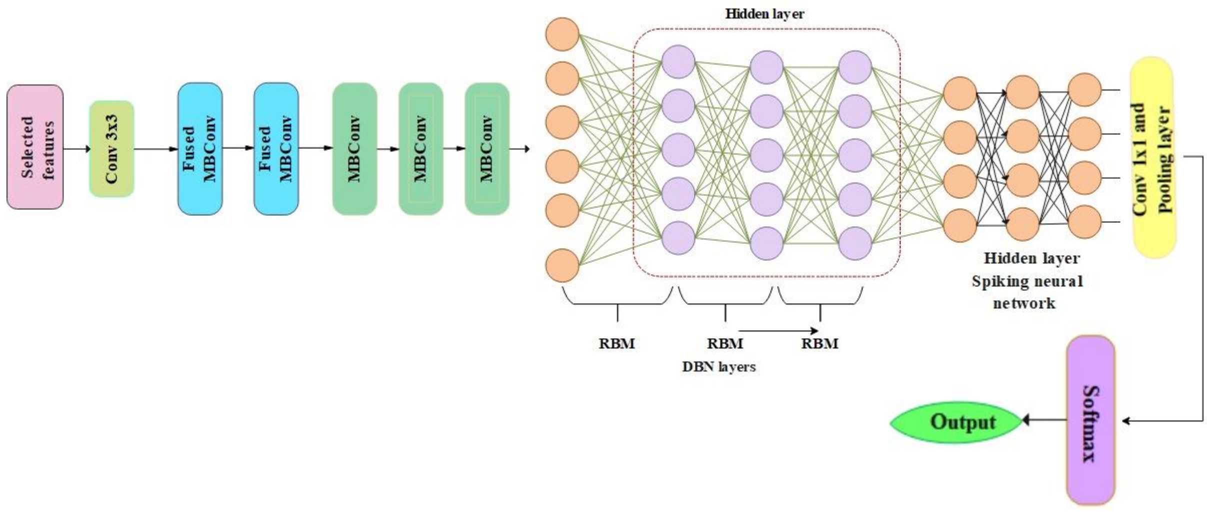

Fig.2. Detailed architecture of the EEGEffV2-SpikeNet model.

The architecture begins with the selected features from preprocessed EEG data, which pass through an initial 3x3 convolutional layer to extract local spatial patterns. Two Fused MBConv blocks then efficiently extract features using depthwise separable convolutions and channel attention, followed by two regular MBConv blocks to abstract deeper features. A 1x1 convolution and pooling layer then reduce the dimensionality while retaining key information. The extracted features are passed through a Deep Belief Network (DBN) with three stacked Restricted Boltzmann Machines (RBMs) to learn high-level representations, followed by a Spiking Neural Network (SNN) that processes temporal dynamics with bio-inspired spike-based mechanisms. The output layer finally classifies the EEG signals as depressed or non-depressed, completing a hybrid approach that combines EfficientNetV2's spatial efficiency with the temporal processing capabilities of SNNs.

The initial layer of the architecture is a 3x3 convolutional layer designed to extract spatial features from the input EEG. Convolution operation here plays a fundamental role in sensing neighborhood patterns and neighborhood interelectrode relations so that an indication about brain activity is developed. Next, there are successive occurrences of many Fused MBConv blocks, one of the critical components in the architecture of EfficientNetV2. These blocks are meant to extract features efficiently with minimal computational expense. They integrate depthwise separable convolutions with squeeze-and-excitation (SE) layers, enabling the model to extract increasingly deeper and more sophisticated features from the EEG signals. Fig 3 illustrates the architecture diagram of EEGEffV2-SpikeNet model, which integrates EfficientNetV2 and Spiking Neural Networks (SNNs) for EEG signal categorization.

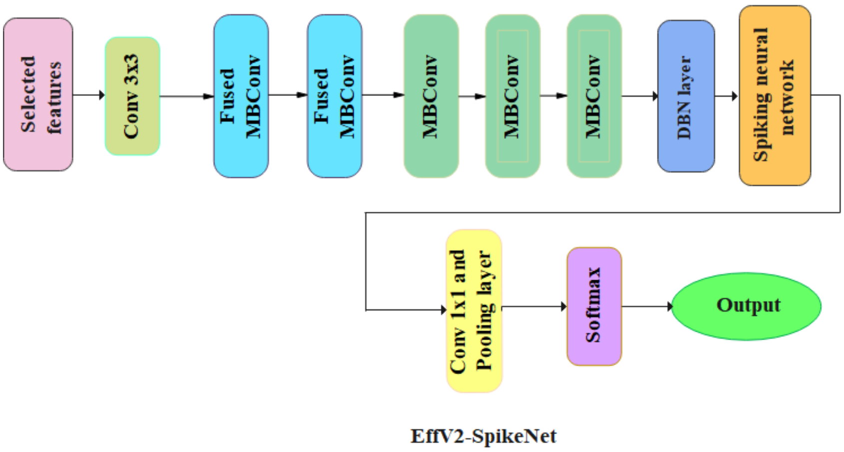

Fig.3. Architecture of the EEGEffV2-SpikeNet Model

The "fused" form of MBConv also streamlines the architecture by combining some operations, which makes it especially well-suited to deal with the high-dimensional nature of EEG data. Following the MBConv blocks, the architecture contains a 1x1 convolutional layer, acting as a bottleneck layer to decrease. The feature maps' dimensions but save key information. This is then followed by a pooling layer, possibly a global average pooling layer, summarizing spatial information from the feature maps and decreasing their dimensions in preparation for the last stages of processing. After the MBConv block, the features are sent to a Deep Belief Network (DBN) layer. Fig. 4 shows the layers of DBN with SNN.

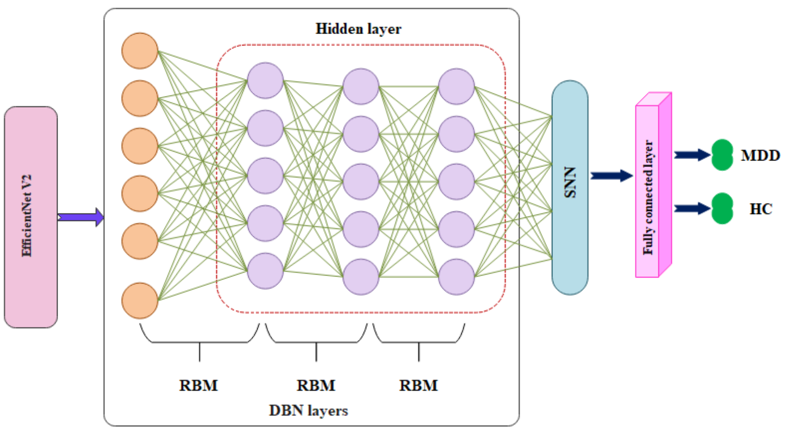

Fig.4. EEGEffV2-SpikeNet Model showing arrangement of DBN and SNN network

DBNs are generative models consisting of several Restricted Boltzmann Machines (RBMs), which can learn high-dimensional dependencies. The DBN layer in EEGEffV2-SpikeNet learns latent representations of EEG data, enhancing the model's discriminability between different mental states. A DBN is made up of multiple RBMs, an undirected generative probabilistic model that models the probabilistic distribution of visible variables using one hidden layer and one hidden layer. High-level features from the data are extracted by our DBN through the processing of information hierarchies using a stack of RBMs.

The RBM transforms inputs into a higher-level feature representation by using an encoder and an encoding-decoding pattern. After that, the input can be rebuilt by the decoder. A significant benefit of DBN is RBM training through input data reconstruction, which is an unsupervised process that doesn't require labeled data. The RBM is composed of a set of hidden units, $h \in \{0.1\}^{g_h}$, and a set of visible units, $v \in \{0.1\}^{g_v}$.The numbers g_h and g_v g_v represent the hidden and visible factor, respectively. The joint configuration $\{v, h\}$ energy in RBM, taking bias into account, is

$$E(v, h) = -v^T W h - b^T v - c^T h \tag{23}$$

The vectors h and x denotes the hidden and visible unit values, W represent the weight matrix, b and c represent the bias vectors for visible and hidden units, respectively. The visible and hidden unit activators are separate entities that do not depend on one another.

$$P(h|v) = \prod_{j=1}^{g_h} P(h_j|v) \tag{24}$$

The distribution of the other layer is factorial if one layer is stated, it should be noted. Given that neurons are binary, the likelihood that a hidden neuron is "on" (value = 1) is as follows:

$$P(h_j = 1|v) = \delta(c_j + \sum_i W_{ij} v_i) \tag{25}$$

where $\delta(x) = 1/(1 + exp(-x))$ is a logistic sigmoid function. Comparably, the following equation (12) is the conditional likelihood of a visible node in relation to the hidden vector:

$$P(v_i = 1|h) = \delta(b_i + \sum_j W_{ij} h_j) \tag{26}$$

Then the architecture then uses a SNN, which is biologically motivated and mimics how the neurons in the brain communicate through spikes. The SNN is effective in extracting temporal patterns and non-regular dynamics in EEG signals, which are critical in unraveling the complex brain activity associated with depression. Through the use of the SNN's temporal processing capability, the model enhances its feature representation and decision capability. Finally, the architecture concludes with a softmax layer, providing the probability distribution across the classes (i.e., depressed or not depressed). Softmax function ensures that output values are normalized and can be interpreted as probabilities, providing a crisp class decision. The output of the architecture is the class decision, i.e., whether the input EEG signal corresponds to a depressed or non-depressed individual.

4. Results

The proposed model is implemented in Python. The EEGEffV2-SpikeNet framework was tested with two publicly accessible EEG datasets to compare its performance in depression detection. The experiments were designed for four most important metrics accuracy, F1-score, recall, and precision in addition to computational efficiency (training time). The results were compared with baseline models such as Deep Belief Networks (DBN), EfficientNet, Spiking Neural Networks (SNNs), and conventional machine learning models (e.g., KNN, SVM, Decision Tree). Common machine learning classification algorithms like KNN, SVM, Decision Tree, Random Forest, and Gradient Boosting were chosen because they are regularly mentioned in EEG studies and serve as strong comparators to test the strength of deep learning models. From the deep learning baselines, Deep Belief Networks (DBN), EfficientNet, and Spiking Neural Networks (SNN) were specifically selected to analyze the roles of hierarchical feature learning, computationally-efficient convolutional architectures, and biologically-plausible temporal processing, respectively.

4.1. Dataset Description

Dataset 1

The Raw EEG Stress Dataset (SAM40) on Kaggle comprises electroencephalogram (EEG) signals from 40 healthy subjects (20 male and 20 female) aged 18-30 years. The data were recorded with a 14-channel Emotiv EPOC+ headset at 128 Hz sampling. All the participants went through a stress experiment consisting of a mix of mental arithmetic projects and the Trier Social Stress Test (TSST), a standard psychological stress protocol. The raw EEG signals are given in .csv files, split into baseline (relaxed) and stress phases to enable comparison of brain activity under various conditions. Other metadata, including self-reported stress ratings (SAM ratings), are added to confirm the induction of stress. This dataset can be utilized for stress detection, emotion recognition, and neurofeedback studies in affective computing and biomedical engineering.

Dataset 2

EEG-Based Stress Detection Dataset by Mendeley is a dataset consisting of electroencephalogram (EEG) recordings that were obtained from 20 healthy subjects (10 males and 10 females) aged among 20 and 30 years. The data were recorded employing a 14-channel Emotiv EPOC+ EEG headset at a sample rate of 128 Hz. In the experiment, stress was induced using cognitive tasks (mathematical problems) and emotional stressors, while EEG signals from participants were recorded in both resting (baseline) and stress states. The dataset consists of raw .csv EEG signals and pre-processed features including bandpower (alpha, beta, gamma, theta) and statistical metrics for machine learning purposes. On top of that, self-assessment manikin (SAM) ratings were gathered to quantify perceived stress levels, which serve as ground truth for stress classification. The dataset can be utilized for stress detection, affective computing, and neuroergonomics studies, facilitating the implementation of machine learning models in mental state analysis. Though the proposed EEGEffV2-SpikeNet framework performs very well on all the used EEG sets, there exist some limitations from a dataset point of view, which need to be mentioned in terms of generality. Both sets have been recorded from small groups of healthy young people within a short age bracket (18-30 years) using a common low-cost EEG recording device (Emotiv EPOC+). The representations learned from this dataset might therefore reflect population-specific neurophysiological patterns and device-dependent signal characteristics. These may limit the direct generalization of findings to older adults, clinically diagnosed depressive patients, or people from other cultural, socioeconomic, or neurological backgrounds.Further, the data were collected based on controlled experimental methods of stress induction, rather than in more realistic clinical conditions of depressive disorder presentation that could capture their complexities of comorbidities in real life. In addition, the binary classification of stress or depression based on self-reported scales can be subjective in terms of labeling bias. The evaluation metrics listed below are used to evaluate the proposed strategy:

Accuracy: Accuracy is calculated as the ratio of successfully identified samples to all samples.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{27}$$

Precision: Precision is defined as the ratio of samples correctly recognized as positive out of all samples foretold to be positive.

$$Precision = \frac{TP}{TP+FP} \tag{28}$$

Recall: A statistic used to evaluate classification problems, recall quantifies how well a model recognizes all relevant cases in the dataset.

$$Recall = \frac{TP}{TP+FN} \tag{29}$$

F-Measure: It is the harmonic mean of recall and precision

$$F - Measure = \frac{2*precision*recall}{Precision+recall} \tag{30}$$

4.2. Performance Comparison of EXISTING Machine Learning Models on Two Datasets

The performance of eight machine learning models is shown in Fig. 5. On Dataset 1, MLP, XGBoost, Gradient Boosting, Random Forest, Decision Tree, SVM, KNN and Logistic Regression were evaluated using four crucial metrics: F1 Score, Accuracy, Precision, and Recall.

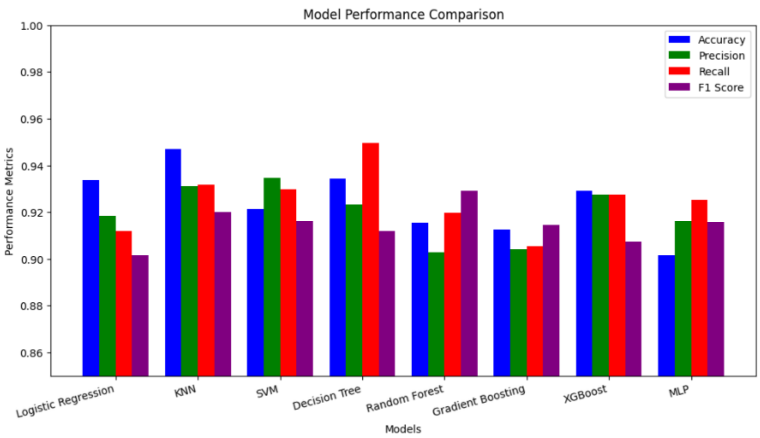

Fig.5. Performance metrics comparison of existing models on Dataset 1

KNN had the best accuracy of 0.9469 and F1 Score of 0.9202, reflecting excellent overall performance and well-balanced trade-off between precision and recall. It also exhibited competitive precision of 0.9311 and recall of 0.9318, reflecting robustness in both the detection of true and false positives/negatives.

Eight different machine learning models are compared in Fig. 6. MLP, XGBoost, Gradient Boosting, Random Forest, Decision Tree, SVM, KNN and Logistic Regression on Dataset 2 were evaluated according to four crucial metrics: F1 Score, Recall, Accuracy, and Precision.

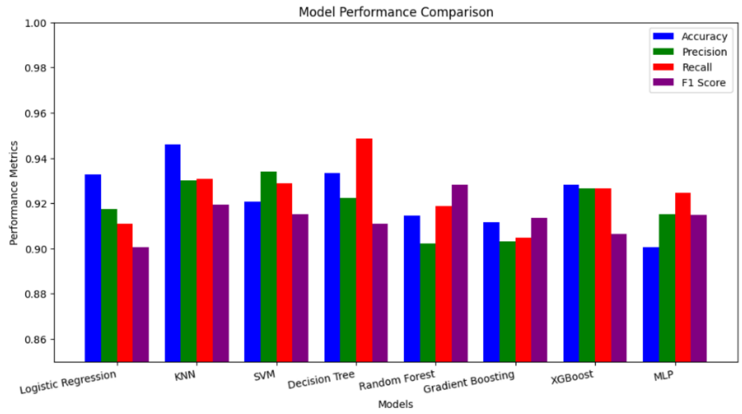

Fig.6. Performance metrics comparison of existing models on Dataset 2

KNN is once again the best performing model with the best accuracy of 0.946 and F1 score of 0.9193, followed closely by Decision Tree accuracy of 0.9334, F1 score of 0.911. KNN also performs well with precision of 0.9302 and recall of 0.9309, reflecting a good capability for correct classification of both positive and negative instances.

4.3. Performance Analysis of Deep Learning Models on Two Datasets

Fig. 7 depicts the bar graph comparison of performance metrics (e.g., accuracy, precision) of the proposed EEGEffV2-SpikeNet model against baseline deep learning models on Dataset 1.

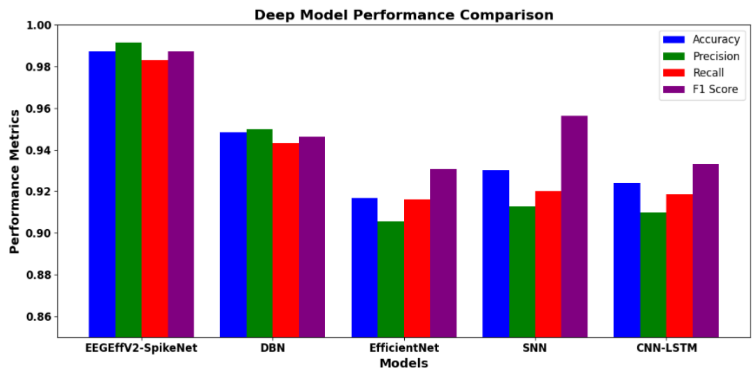

Fig.7. Bar chart comparing the performance metrics of the proposed EEGEffV2-SpikeNet model against baseline models for Dataset 1

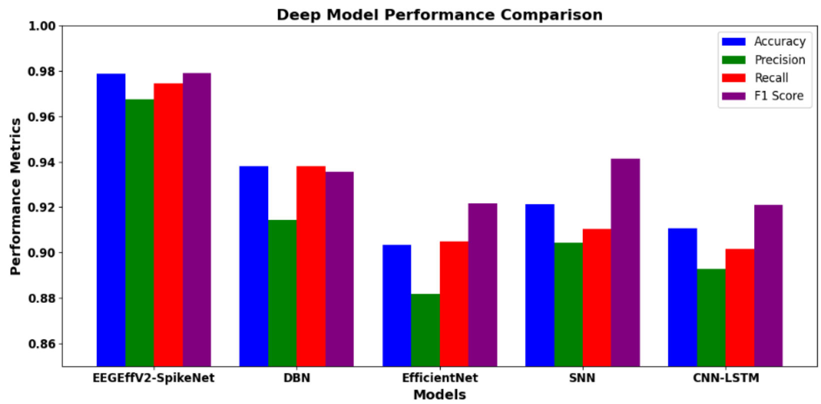

Fig.8. Bar chart comparing the performance metrics of the proposed EEGEffV2-SpikeNet model against baseline models for Dataset 2

The proposed EEGEffV2-SpikeNet model shows better performance on Dataset 1. EEGEffV2-SpikeNet achieved the highest performance among all the deep learning models studied for classifying depression. It recorded better performance with an accuracy of 0.9861, precision of 0.9912, recall of 0.9833, and an F1-score of 0.9871. These results indicate that the model is highly reliable, with excellent ability to correctly identify depressed and non-depressed cases with minimal error.

Fig. 8 depicts the bar graph comparison of performance metrics (e.g., accuracy, precision) of the proposed model against baseline models on Dataset 2.

The proposed EEGEffV2-SpikeNet model shows outstanding performance on Dataset 2 among all models for depression classification. It achieved an accuracy of 0.9793, precision of 0.9671, recall of 0.9740, and an F1-score of 0.9796. These high metric values indicate the model's strong reliability and effectiveness. Fig. 9 displays the training time comparison between the proposed model and baseline models on Dataset 1.

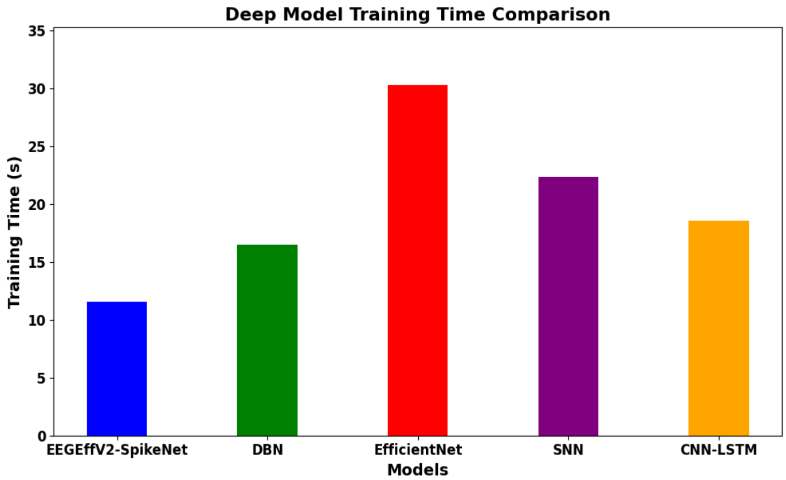

Fig.9. Bar chart comparing the training times of the proposed EEGEffV2-SpikeNet model and baseline models on Dataset 1

The training time measures indicate dramatic variations in computational efficiency among the models under consideration, with the proposed EEGEffV2-SpikeNet performing best at only 11.56 seconds, much quicker than all the comparison models. Fig. 10 displays the training time comparison between the proposed and baseline models on Dataset 2.

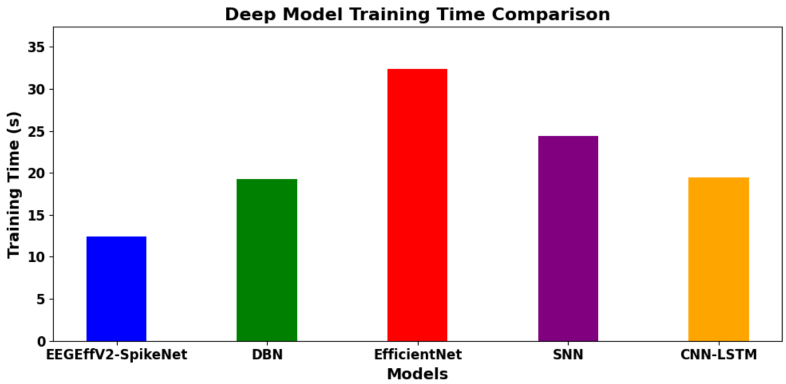

Fig.10. Bar chart comparing the training times of the proposed EEGEffV2-SpikeNet model and baseline models on Dataset 2

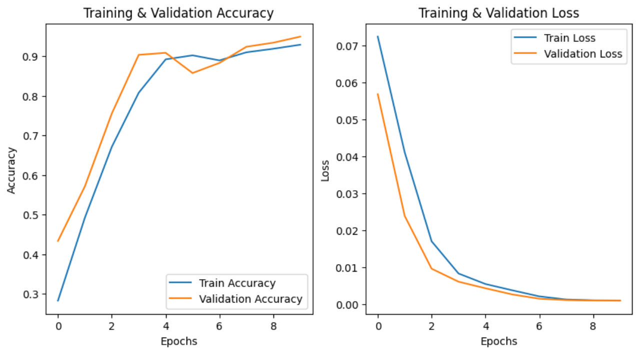

Fig.11(a). Training and validation accuracy and loss for Dataset 1

The proposed **EEGEffV2-SpikeNet** model achieved the lowest training time of 12.34 seconds, outperforming other models on Dataset 2.

Fig. 11(a) shows that the training and validation accuracy plots for Dataset 1 exhibit a steep rise during the initial five epochs, with training accuracy increasing from approximately 0.28 to 0.91 and validation accuracy rising from 0.47

to 0.92.

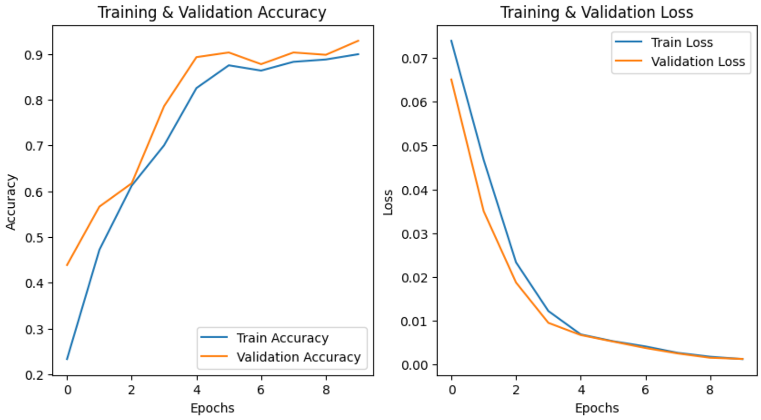

Fig.11(b). Training and validation accuracy and loss for Dataset 2

Fig. 11(b) shows that the training and validation accuracy plots for Dataset 2 exhibit a steep rise during the initial five epochs, with training accuracy increasing from approximately 0.25 to 0.89 and validation accuracy rising from 0.45 to 0.91.

Fig. 12 displays the Receiver Operating Characteristic (ROC) curves that evaluate the diagnostic performance of EEGEffV2-SpikeNet on both datasets.

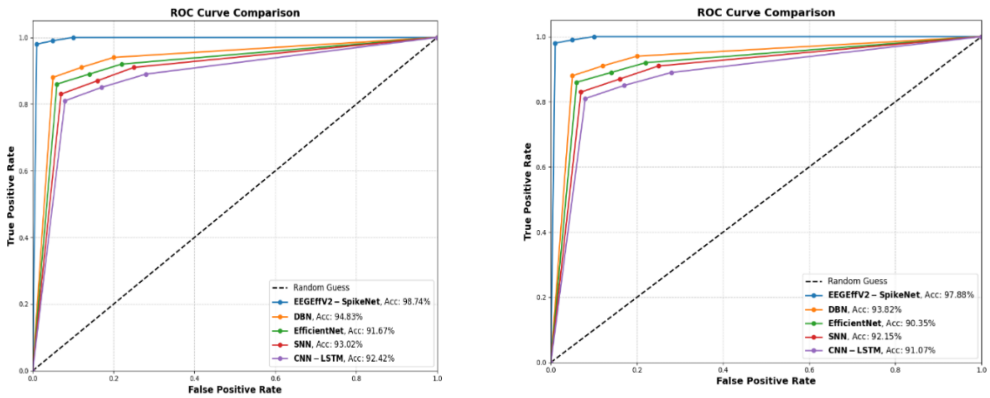

Fig.12. ROC curves for Dataset 1 and Dataset 2

The ROC curve shows that EEGEffV2-SpikeNet is more capable of accurately distinguishing between healthy and depressed classes, making it the best among the compared models for the task.

Although accuracy, precision, recall, and F1-score offer a numerical measure of the model performance, the consequences of these metrics in the real-world diagnosis deserve more attention. Since recall (sensitivity) is crucial in depression diagnosis, a low false negative rate ensures that depressed patients are not overlooked. Thus, the high recall achieved by the EEGEffV2-SpikeNet model enhances its effectiveness as an early diagnostic or warning system, helping to avoid the high costs associated with missed diagnoses in depressed patients. On the other hand, precision is known to represent the reliability level of positive predictions. Low precision may lead to false alarms, thereby increasing clinical workload and potentially causing unnecessary anxiety among patients. The balanced precision and recall demonstrated by the proposed model suggest its potential to reduce unnecessary referrals while ensuring patient safety. This is supported by the F1-score, which is the harmonic mean of precision and recall, providing a robust metric for evaluating performance on imbalanced datasets common in mental health diagnoses. Practically, the combination of high accuracy and optimal computational efficiency makes the model suitable for real-time or near-real-time clinical systems. Notably, the proposed approach is not intended to replace psychiatrists but rather to serve as a useful and objective adjunct for assisted diagnostic services.

Table 1 shows the ablation study results to emphasize the role of each component in the proposed EEGEffV2-SpikeNet model. Removing the Graph Convolutional Network (GCN) resulted in a significant accuracy drop to 94.20% (F1-score: 0.938), highlighting the importance of capturing connectivity among EEG electrodes to identify distinguishing brain graph patterns for depression. The removal of the Modified Addax Optimization Algorithm (MAOA) led to a moderate performance degradation (accuracy: 96.80%, F1-score: 0.965) and increased inference time, demonstrating MAOA's effectiveness in removing redundant features and reducing complexity. The use of LSTM instead of SNN causes only a mediocre deterioration (accuracy: 97.10%, F1-score: 0.969) with a massive increase in inference time (15.3 s), thus verifying once again the superiority of spike train modeling over standard SNN modeling. In contrast, the complete EEGEffV2-SpikeNet achieved the highest accuracy of 98.74% and an F1-score of 0.987, with a balanced inference time of 11.56 s. It is evident from the ablation study results that the collective integration of GCN, MAOA, and SNN is responsible for achieving higher accuracy, robustness, and efficiency in the proposed design.

Table 1. Ablation analysis of the proposed model

Model Variant	Accuracy	F1-Score	Inference Time
Without GCN	94.20%	0.938	8.9s
Without MAOA	96.80%	0.965	12.1s
Without SNN (replaced with LSTM)	97.10%	0.969	15.3s
Full EEGEffV2-SpikeNet	98.74%	0.987	11.56s

5. Conclusions

The proposed EEGEffV2-SpikeNet is a deep learning hybrid framework that integrates EfficientNetV2, DBN, and SNNs for depression detection from EEG, incorporating a GCN to represent brain connectivity and the MAOA for optimal feature selection. A strong preprocessing pipeline (notch filtering, WPT, and CCA) provides clean EEG signals, and the hybrid architecture takes advantage of EfficientNetV2's efficiency and SNN's temporal processing for improved performance. The results show that EEGEffV2-SpikeNet surpasses baseline models, recording an accuracy of 0.9874 in Dataset 1 and 0.9788 in Dataset 2, with high precision, recall, and F1-scores. Furthermore, the model demonstrates superior computational efficiency, requiring significantly less training time (11.56 seconds for Dataset 1 and 12.43 seconds for Dataset 2) compared to traditional models such as DBN, EfficientNet, and SNN. These results demonstrate the framework's capability to effectively classify EEG signals into depressed and non-depressed categories, making it a feasible tool for clinical applications. This research is significant for mental health diagnosis, providing a non-invasive, efficient, and objective tool for early depression detection. The model's high accuracy and low false positive rate decrease the chances of misdiagnosis, and its computational efficiency enables deployment in real-world settings. Future work will focus on generalizing the framework to other neurological disorders, such as anxiety or schizophrenia, by adapting the feature extraction and classification modules. Further validation on larger, more diverse datasets, as well as multi-modal data (e.g., combining EEG with fMRI or behavioral markers), will be conducted to enhance the model's generalizability.

All the Declarations and Statements

Author Contributions Statement

Alphonsa Sini P J- Conceptualization, Methodology, Data Curation, Software, Formal Analysis, Writing – Original Draft.
Dr Sherly K K - Validation, Investigation, Resources, Visualization, Writing – Review & Editing.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no competing interests.

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Data Availability Statement

No datasets were generated or analyzed during the current study.

Ethical Declarations

Not Applicable

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Declaration of Generative AI in Scholarly Writing

The authors declare that no Generative Artificial Intelligence (AI) tools or technologies were used in the preparation, writing, analysis, or editing of this manuscript. This manuscript represents the original work of the authors.

Abbreviations

The following abbreviations are used in this manuscript:

EEG - Electroencephalography
GCN - Graph Convolutional Network
MAOA - Modified Addax Optimization Algorithm
DBN - Deep Belief Network
SNN - Spiking Neural Network
DD - Depressive Disorder
GAD - Generalized Anxiety Disorder
WHO - World Health Organization
ML - Machine Learning
DL - Deep Learning
LORETA - Low-Resolution Electromagnetic Tomography
WPT - Wavelet Packet Transform
CCA - Canonical Correlation Analysis
MDD - Major Depressive Disorder
DAL - Domain Adversarial Learning
DNN - Deep Neural Network
LSTM - Long Short-Term Memory
MLR - Multiple Linear Regression
DAMGCN - Dual Attention Mechanism Graph CNN
DWT - Discrete Wavelet Decomposition
COIWSO - Chaotic Owl Invasive Weed Search Optimization
SA-GDensenet - Self-Attention-based Gated Densenet
HEMAsNet - Hemisphere Asymmetry Network
FCAN - Functional Connectivity Attention Network
CN-BO - CNN with Bat Optimization
PSD - Power Spectral Density
GA - Genetic Algorithm
PSO - Particle Swarm Optimization
SE - Squeeze-And-Excitation
RBMs - Restricted Boltzmann Machines
TSST - Trier Social Stress Test
SAM - Self-Assessment Manikin
ROC - Receiver Operating Characteristic

Appendix

Not Applicable

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